

COMPARATIVE ANALYSIS OF CONVENTIONAL AND INTELLIGENT METHODS FOR OPTIMAL POWER FLOW

V. AKHILA¹ & M. NAGA JYOTHI²

¹Research Scholar, Department of Power Electronics, VNR VJIET, Hyderabad, Telangana, India

²Assistant Professor, Department of EEE, VNR VJIET, Hyderabad, Telangana, India

ABSTRACT

In this paper an algorithm for solving optimal power flow problem through the application of a Genetic Algorithm (GA). The objective of an optimal power flow (OPF) is to find steady state operation point which minimizes total generating unit (thermal) fuel cost and the real power loss while maintaining an acceptable system performance in terms of limits on generator real and reactive power outputs. Genetic Algorithm is one of evolutionary algorithms, which has been used in many optimization problems due to its simplicity and efficiency. To test the efficacy of the algorithm, it is applied to IEEE30-bus power system. The optimal power flow results obtained using GA are compared with conventional methods. The simulation results reveal that the GA optimization technique provides better results when compared to other conventional methods.

KEYWORDS: Fuel Cost Minimization, Genetic Algorithm, Optimal Power Flow, Conventional Gradient Method

INTRODUCTION

Optimal Power Flow (OPF) was first discussed by Carpentier in 1962. In the past two decades; OPF problem has received much attention due to the need for fast and robust optimization tools that consider both security and economy are more demanding than before to support the system operation and control while satisfying various engineering and economic constraints.

Optimization methods have been widely used in power system operation, analysis and its planning. One of the most applications of it is optimal power flow. It is a particular mathematical approach which aims to optimize a selected objective function via optimal adjustments of the power system control variables to keep power system at the most desired state while satisfying various equality and inequality constraints.

OPF Problem

Generally, most of the conventional methods apply sensitivity analysis by linearizing the objective function and system constraints around an operating point. Unfortunately, OPF is modeled as a nonlinear programming (NLP) problem and multi-model optimization problem. The solution has more than one local optimum solution. OPF is a non-linear, non-convex, non-differentiable large-scale objective functions. so, in order to overcome such difficulties so the implementation of Intelligent methods came into existence.

Recently, Evolutionary optimization techniques have been used to solve the OPF problem in order to overcome the Limitations due to convention methods. A wide range of traditional optimization techniques such as linear

programming, Non-linear programming, quadratic programming, Newton method, dynamic programming, mixed-integer programming, decomposition technique and interior point method. The results obtained from Evolutionary techniques are more promising and effective for further research.

The most commonly used evolutionary optimization technique is the Genetic Algorithm (GA). It provides a near optimal solution for a complex problem having large number of variables and constraints, which cannot be solved by using Linear programming or gradient methods. Because of determining the optimum controlling parameters such as population size, crossover rate and mutation rate. This is easy to implement, Flexible and takes less time.

The Genetic algorithm (GA) algorithm is a simple yet powerful population-based stochastic search technique, which is an efficient and effective global optimizer in the continuous search domain as it works on coding of the parameter set so they can handle integer and discrete variables. It searches within a population of points within limits so it is a globally optimal solution as it uses probabilistic transition rules, not deterministic rules.

Problem Formulation of OPF

The solution of OPF problem aims to optimize a selected objective function via optimal adjustments of power system control variables while satisfying various equality and inequality constraints. Mathematically the OPF problem can be formulated as:

$$\text{Min } J(x, u) \quad (1)$$

$$\text{Subject to: } g(x, u) = 0 \quad (2)$$

$$h(x, u) \leq 0 \quad (3)$$

Where J is the objective function to be minimized. There the objective function is Fuel cost of generating units.

Minimization of Fuel Cost of Generating Units

The fuel cost minimization can be formulated as

$$F_1 = \text{Minimize } FC(P_g) = \sum_{i=1}^{N_g} FC_i(P_{gi}) \quad (4)$$

Where $FC(P_g)$ = Total fuel cost of generating units

$FC_i(P_{gi})$ = Fuel cost function of i^{th} generator

$$= a_i P_{gi}^2 + b_i P_{gi} + c_i \quad (5)$$

Where a_i, b_i, c_i : Fuel cost coefficient of i^{th} generator

P_{gi} : Real power generation of i^{th} generator

N_g : Number of generators (thermal) including the slack.

System Constraints

The minimisation of above objective function is subjected to various equality and inequality constraints.

x is the vector of dependent variables (state vector) consisting of:

- Generator active power output at slack bus P_{G1} .
- Load bus voltage V_L .
- Generator reactive power output Q_G .
- Transmission line loading (or line flow) S_L .

Hence, x can be expressed as

$$x^T = [P_{G1}, V_{L1}, V_{LNL}, Q_{G1}, Q_{GNG}, S_{L1}, S_{LNL}] \quad (6)$$

Where, NL , NG , and nl are the number of load buses, number of generators, and number of transmission lines, respectively

u is the vector of independent variables (control variables) consisting of

- Generation bus voltages V_G .
- Generator active power output P_G at PV buses except at the slack bus P_{G1} .
- Transformer tap settings T .
- Shunt VAR compensation QC .
- Hence, u can be expressed as:

$$u^T = [P_{G2}, P_{GNG}, V_{G1}, V_{GNG}, Q_{C1}, Q_{CNC}, T_1 \dots T_{NT}] \quad (7)$$

Where NT and NC are the number of the regulating transformers and VAR compensators, respectively.

Equality Constraints

g these are the equality constraints, which represent typical load flow equations:

$$PG_i - PD_i - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \quad (8)$$

$$QG_i - QD_i - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0 \quad (9)$$

Where NB is the number of buses, PG is the active power generation,

Q_G is the reactive power generation; PD is the active load demand,

Q_D is the reactive load demand, G_{ij} and B_{ij} are the conductance and susceptance between bus i and bus j , respectively.

Inequality Constraints

h these are the inequality constraints that include:

- Generator constraints: generation bus voltages, active power outputs, and reactive power outputs are restricted by their lower and upper limits as:

$$V_{Gi}^{\min} \leq V_{Gi} \leq V_{Gi}^{\max} \quad i = 1..NG \quad (10)$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad i=1, \text{NG} \quad (11)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad i=1, \text{NG} \quad (12)$$

- Transformer constraints: Transformers tap settings are restricted by their lower and upper limits as:

$$T_i^{\min} \leq T_i \leq T_i^{\max} \quad i=1, \text{NT} \quad (13)$$

- Shunt VAR constraints: shunt VAR compensations are restricted by their limits as:

$$Q_{Ci}^{\min} \leq Q_{Ci} \leq Q_{Ci}^{\max}, \quad i=1, \text{NC} \quad (14)$$

Security constraints: Include the constraints of voltages at load buses and transmission line loadings:

$$V_{Li}^{\min} \leq V_{Li} \leq V_{Li}^{\max} \quad i=1, \text{NL} \quad (15)$$

$$S_{li} \leq S_{li}^{\max} \quad i=1, \text{nl} \quad (16)$$

CONVENTIONAL METHODS

Traditionally, conventional methods are used effectively to solve OPF. The application of these methods had been an area of active research in the recent past. The conventional methods are based on mathematical programming approaches and used to solve different size of OPF problems. In order, to meet the requirements of different objective functions, types of application and nature of constraints.

Generally, most of the classical optimization techniques apply sensitivity analysis and gradient-based optimization algorithms by linearizing the objective function and the system constraints around an operating point.

Conjugate Gradient Method (CGM) computational flow

The main features of Conjugate Gradient Method (CGM) can be stated as follows:

- Set any values of lambda.
- Solve for the value of power generation or dispatch using the equation of power that we have to formulate.
- Compute the mismatch or the absolute value of the difference between actual load and the sum of the computed power generators.

CGM for Equality constraints

The CGM Method can solve optimization problems with equality constraints:

$$\text{Min } J(x, u)$$

$$\text{Subject to: } g(x, u) = 0 \quad j=1, m < n$$

The CGM function is as follow

$$L(x, \lambda) = J(x) + \sum_{j=1}^m \lambda_j h_j(x) = f(x) + \lambda^T h(x) \quad (17)$$

Where λ is an $m \times 1$ vector of Lagrange multipliers, one for each constraint. In general, we can set the partial derivatives to zero to find the minimum.

CGM for Inequality Constraints

The augmented Lagrange method combines the classical Lagrange method with the penalty function method. CGM method to tackle inequality constraints for the problem:

$$\text{Min } J(x, u)$$

$$\text{Subjected to: } h(x, u) \leq 0 \quad i = 1:p$$

One possible augmented Lagrangian function given by

$$L(x, \lambda, \rho) = f(x) + \sum_{i=1}^p [\max(1/2\lambda_i + \rho g_i(x), 0)]^2 \quad (18)$$

Where λ are the Lagrange multipliers and ρ is an adjustable penalty parameter. [Greig 1980] gives a slightly different formulation, but retains the same concept. A comparison of the partial derivatives of the augmented Lagrange and the classical Lagrange functions produces the following iterative approximation for:

$$\lambda^* \equiv \lambda_{K+1} = \max(\lambda_K + 2\rho g(x^*_K), 0) \quad (19)$$

Then the CGM algorithm is followed to achieve the optimization. This method is implemented by using the MATLAB Software by coding.

Significance of CGM

- The Gradient procedure is used to find the optimal power flow solution that is feasible with respect to all relevant inequality constraints. It handles functional inequality constraints by making use of penalty functions.
- Gradient methods are better fitted to highly constrained problems.
- Gradient methods can accommodate non linearities easily compared to Quadratic method.
- Compact explicit gradient methods are very efficient, reliable, accurate and fast.
- This is true when the optimal step in the gradient direction is computed automatically through quadratic developments.
- This method shown less computation time, with a tolerance of 0.001, when compared to other penalty function techniques.

Generally, most of the classical (Namely Conventional) optimization techniques apply sensitivity analysis and gradient-based optimization algorithms by linearizing the objective function and the system constraints around an operating point. Unfortunately, the OPF problem is a highly non-linear and multi-modal optimization problem, i.e., there is more than one local optimum. Hence, the intelligent methods came into existence to overcome this problem.

INTELLIGENT METHODS

These Methods are generally population based optimization algorithms find near optimal solutions to the difficult optimization problems by motivation from nature and modified by applying the operators on the solutions depending on the information of the fitness moving towards the better solution region of the search space. In this Paper we are taking one of the efficient, accurate and less time consuming Intelligent Method, Genetic Algorithm

Genetic algorithms are search algorithms based on the process of biological evolution. In genetic algorithms, the mechanics of natural selection and genetics are emulated artificially. The search for a global optimum to an optimization problem is conducted by moving from an old population of individuals to a new population using genetics-like operators. Each individual represents a candidate to the optimization solution. An individual is modeled as a fixed length string of symbols, usually taken from the binary alphabet.

Genetic Algorithm Computational Flow

The main features of Genetic Algorithm (GA) can be stated as follows

Initialization

Initialize population size, maximum generation, stall time limit and read the cost coefficients and B coefficients or Loss coefficients.

Formation of Population

The initial power search for each generator can be obtained by

$$P_{ij} = P_{imin} + \{(P_{imax} - P_{imin}) / (2l-1)\} * b_{ij} \quad (20)$$

Where,

i = number of generator

j = number of generation

Evaluate the Fitness Function.

The incremental transmission losses denoted as 'B' is calculated as per formula the given below and determines the best fitness and mean fitness values.

Apply Genetic Operators

Parent individuals are selected using 'Roulette Wheel' selection procedure and single point crossover is used and finally mutation operator is used for regaining the lost characteristics during the process.

Repeat the step 3 and step 4 until the process has been converged or it satisfies the stopping criteria

The process undergoing in GA is shown in Figure 1

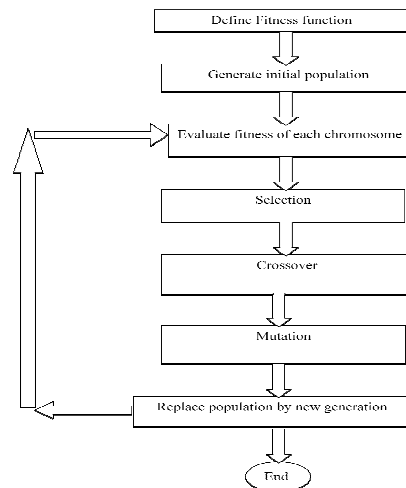


Figure 1: Genetic Algorithm Cycle of Stages

Initialization

The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Often, the initial population is generated randomly, allowing the entire range of possible solutions (the *search space*). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

Selection

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solution are selected through a fitness based process. The fittest one are typically more likely to be selected. The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent.

Genetic Operators

The next step is to generate a second generation population of solutions from those selected through a combination of genetic operators cross over (namely known as recombination) and mutation.

Cross Over

Crossover is the primary genetic operator, which promotes the exploration of new regions in the search space. For a pair of parents selected from the population the recombination operation divides two strings of bits into segments by setting a crossover point at random, i.e. Single Point Crossover. The segments of bits from the parents behind the crossover point are exchanged with each other to generate their offspring. The mixture is performed by choosing a point of the strings randomly, and switching their segments to the left of this point.

Mutation

Mutation is a secondary operator and prevents the premature stopping of the algorithm in a local solution. It is a random bit value change in a chosen string with a low probability of such change. The mutation adds a random search character to the genetic algorithm, and it is necessary to avoid that, after some generations, all possible solutions were very similar ones. All strings and bits have the same probability of mutation. In mutation, the solution may change entirely from the previous solution.

The purpose of mutation in GAs is preserving and introducing diversity. Mutation should allow the algorithm to avoid local minima by preventing the population of chromosomes from becoming too similar to each other, thus slowing or even stopping evolution. This reasoning also explains the fact that most GA systems avoid only taking the fittest of the population in generating the next but rather a random (or semi-random) selection with a weighting toward those that are fittest.

Reproduction

Reproduction is based on the principle of survival of the better fitness. It is an operator that obtains a fixed number of copies of solutions according to their fitness value. If the score increases, then the number of copies increases too. A score value is associated to a given solution according to its distance of the optimal solution (closer distances to the optimal solution mean higher scores)

By undergoing the entire computational flow the results are found to be more efficient.

RESULTS AND DISCUSSIONS

In this paper comparative analysis of CGM and GE on optimal power flow implemented on IEEE-30 bus system implemented in MI-POWER software shown in figure 2.

The Proposed GE algorithm is developed and implemented using MATLAB software. Initially several runs are done with the following values population size, $L=20$. Cross over probability $P_c=0.8$. Mutation probability,

$P_m=0.01$.

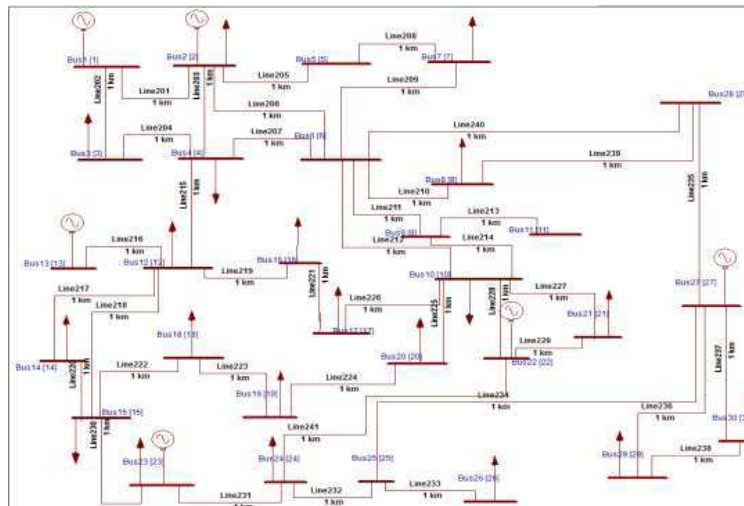


Figure 2: Construction of IEEE-30 Bus System in MI-POWER

By, using information from tables, both the methods are implemented on the IEEE-30 bus system. By, implementing IEEE-30 bus in MI-POWER software by considering all constraints mentioned the cost is 709(\$/h). The comparative results of conventional method and intelligent method is shown in Table 3.

Table 1: Cost Coefficients of IEEE-30 Bus System

Unit	P_1^{\min} (MW)	P_1^{\max} MW (MW)	a (\$/Mwh ²)	b (\$/Mwh)	c
1	50	200	0.00375	2.00	0
2	20	80	0.01750	1.75	0
5	15	50	0.06250	1.00	0
8	10	35	0.00834	3.25	0
11	10	30	0.02500	3.00	0
13	12	40	0.02500	3.00	0

Table 2: Loss Coefficients of IEEE-30 Bus System ($\times 10^4$)

2.18	1	0.9	-1.1	0.2	0.27
1	1	0.4	-1.5	0.2	0.3
0.9	0.4	4.1	-1.31	-1.53	-1.7
-0.1	-1	-1.31	2.21	0.94	0.5
0.2	0.2	-1.53	0.94	2.4	0
2.7	3	-1.7	0.5	0	3.5

Table 3: Comparative Analysis of OPF in CGM & GA

Bus	Dispatched Power(MW)			Fuel Cost(\$/H)		
	CGM Without generator limits	CGM With generator limits	GA	CGM Without generator limits	CGM With generator limits	GA
1	172.83	159.18	125.9	654.9789 (\$/h)	651.2884 (\$/h)	609.884 (\$/h)
2	44.178	41.254	44.24			
5	18.37	17.55	22			
8	2.77	10	24.21			
11	5.9247	10	20.43			
13	5.9247	12	13.42			

CONCLUSIONS

In this paper an attempt has been made to adopt the use of genetic algorithm and conjugate gradient method in optimal power flow. Even though, excellent advancements have been made in classical methods, they suffer in handling qualitative constraints, poor convergence, may get stuck to local optimum, they become too slow if the number of variables are more and computationally more complex. Whereas, the major advantages of the artificial techniques are relatively versatile for handling various qualitative constraints in a simplest manner. In this paper an effort has been modeled to compare the artificial intelligence approach and arrived at a better solution which has a better ability to save the fuel cost and computational time.

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